

University of Groningen

Going for gold

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Published in:
International Journal of Research in Marketing

DOI:
[10.1016/j.ijresmar.2013.09.004](https://doi.org/10.1016/j.ijresmar.2013.09.004)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Final author's version (accepted by publisher, after peer review)

Publication date:
2014

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Gijsenberg, M. J. (2014). Going for gold: Investigating the (non)sense of increased advertising around major sports events. *International Journal of Research in Marketing*, 31(1), 2-15.
<https://doi.org/10.1016/j.ijresmar.2013.09.004>

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Going for gold: Investigating the (non)sense of increased advertising around major sports events

September 20, 2013

International Journal of Research in Marketing

Forthcoming

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The author thanks editor Jacob Goldenberg, the area editor and two anonymous IJRM reviewers for their excellent guidance and valuable suggestions. He also thanks Tammo Bijmolt, Jenny van Doorn, Hans Risselada, Peter Verhoef and Jaap Wieringa for their constructive comments on previous versions of the article, and Marnik Dekimpe, Jan-Benedict Steenkamp and AiMark for providing access to the data.

Going for gold: Investigating the (non)sense of increased advertising around major sports events

Abstract

Major sports events draw unsurpassed media attention. Companies are motivated to increase their advertising investments around these events to reach large audiences in a short period. Is such an advertising surge actually beneficial though, or should companies avoid advertising in these periods because of negative effects of competitive interference? This study investigates when consumer packaged goods companies should invest in advertising to increase sales: before, during, or after the event or outside these event periods. The author estimates *short- and long-term own- and cross-advertising elasticities* for 206 brands using four years of weekly data. Although considerable heterogeneity exists across brands, own-advertising effectiveness diminishes especially before and during major sports events, in both the short and the long run. In addition, brands benefit less from category-demand effects through competitors' advertising. Conversely, greater increases in advertising spending resulting in significant growth in share of voice around focused, single-sport events are a successful strategy to overcome this overall general negative trend.

Keywords: Advertising, Marketing-mix effectiveness, Time series, Empirical generalizations

1. Introduction

Major sports events such as the Super Bowl, the Olympics, and the FIFA World Cup draw unsurpassed media attention. Millions of people follow coverage of these events by watching television, listening to radio, and reading (background) stories in newspapers. The 2006 FIFA World Cup in Germany drew a cumulative audience of 26 billion worldwide (FIFA, 2007). Estimations of people watching the opening ceremony of the 2012 London Olympics amounted to 900 million worldwide (Reuters, 2012), beating the estimated 700 million viewers for the 2010 FIFA World Cup final and the 600 million viewers of the 2008 Beijing Olympics opening ceremony (Reuters, 2010b). Super Bowl XLVI attracted an average of 111.3 million US viewers, making it the most-watched television program in U.S. history (*The Wall Street Journal*, 2012).

Companies are eager to reach such large audiences around these events and increase their advertising investments (Bloomberg, 2011a). The Super Bowl generated \$1,620 million in advertising spending in the first decade of the 21st century, with budgets for Super Bowl XLV amounting to more than \$200 million (Kantar Media, 2011) and companies willing to spend \$3.8 million, on average, for a 30-second commercial during Super Bowl XLVII (*The Wall Street Journal*, 2013). Similarly, estimates of additional advertising expenditures around the 2010 FIFA World Cup amounted to \$1,500 million worldwide (Bloomberg, 2011b).

Are such surges in advertising actually as beneficial to companies as pundits claim? Previous research has found positive effects of Super Bowl advertising on purchase intentions (Russell, Fortunato, Valencia, & Burns, 2003) and movie advertisement effectiveness (Yelkur, Tomkovick, & Traczyk, 2004). However, no study has addressed the question whether companies should concentrate their advertising efforts around such events or focus instead on other periods to increase sales. For example, media rates are higher during these types of events than at other times (e.g., Kantar Media, 2011, 2012; STER, 2010a, 2010b,

2012a, 2012b), as is competitive interference because of the greater number of advertisers and advertising messages (e.g., Danaher, Bonfrer, & Dhar, 2008).

This study systematically investigates whether advertising elasticities change around major sports events and, if so, in what direction and to what extent. It sheds light on the evolutions in both short- and long-term elasticities, focusing not only on own- but also on cross-advertising elasticities. Finally, it investigates whether additional investments to increase share of voice (SOV) around these events are a sound strategy for increased sales.

I conduct a large-scale empirical study using four years of weekly observations for 206 brands in the United Kingdom, across 64 consumer packaged goods (CPG) categories. The study's focus is on "normal" advertising, not on official sponsoring of the event (e.g., Cornwell & Maignan, 1998; Walraven, Bijmolt, & Koning, 2013) or so-called ambush marketing actions (e.g., Payne, 1998). The observed surge in normal advertising is a more widespread phenomenon than the latter cases and, thus, more relevant to companies.

The remainder of this article proceeds as follows: Section 2 provides an overview of the relevant literature. Section 3 describes the econometric model and the techniques used to formulate the empirical generalizations, and Section 4 presents the data. Model-free insights appear in Section 5. Section 6 presents the estimation results and a discussion of advertising elasticity evolutions, including additional insights into the role of media rates, product–event fit, and the usefulness of price discounts. Section 7 provides a discussion of key insights, implications and limitations, and offers suggestions for further research.

2. Effectiveness of advertising around major sports events

2.1. Increased advertising effectiveness

Advertising effectiveness is expected to increase around major sports events simply because advertising messages reach more people more often. Not only are audiences larger, but people also likely see the messages more often because they devote a great amount of

time to these events. Mere exposure effects (Zajonc, 1968) thus could lead to increased effectiveness of advertising. Such effects grow stronger before the event, culminate during the event itself, and then level off, thus showing an inverse U shape.

Category-demand effects may also have a positive impact because categories that have a higher fit (e.g., beer, soft drinks, savory snacks) with the experience of the event should gain higher demand in such periods. In addition, sales effects may be both direct (increased sales from increased category demand) and indirect (increased sales through marketing in the larger market). In the latter case, because of the larger total market (Chevalier, Kashyap, & Rossi, 2003), the potential to attract additional sales through similar advertising investments will also be larger, raising advertising's potential effectiveness.

Furthermore, profound psychological processes may also come into play in major sports events. The media attention these events receive signals their importance to consumers. Thus, consumers are likely to perceive commercial messages surrounding these events as more important and interesting (Kahneman & Tversky, 1973). In turn, they are likely to pay closer attention to these messages. In addition, these events share a strong emotional appeal, which can increase advertising effectiveness in two ways. First, companies try to transfer these positive emotions to their brands (e.g., Grohs, Wagner, & Vsetecka, 2004). By advertising around the event and associating themselves with both the values brought by the event and the consumer emotions triggered by it, companies aim to create positive feelings toward their ads and, hence, their brands (Bagozzi, Gopinath, & Nyer, 1999). This transfer of positive emotions strengthens the position of the brand in consumers' minds, resulting in higher purchase likelihoods (Morris, Woo, Geason, & Kim, 2002). Second, the strong images and associations the event generates in consumers' minds increase the salience of the messages, giving them a stronger weight in decision processes suffering from cue competition (Kruschke & Johansen, 1999).

Findings from previous research on advertising around major sports events confirm an overall positive impact, showing higher brand recall (Bloom, 1998), purchase intentions (Russell et al., 2003), and movie ticket sales (Yelkur et al., 2004). Research also shows that the Super Bowl is of interest when aiming at young male viewers (Tomkovic, Yelkur, & Christians, 2001), whom are otherwise difficult to reach. However, none of these studies includes advertising elasticities. In addition, they are either event studies or cross-sectional in nature. Consequently, their findings cannot be generalized to over-time comparisons.

2.2. Decreased advertising effectiveness

Although clear arguments exist for an increase in advertising effectiveness, some factors may also have a negative effect. First, increases in media rates (Kantar Media, 2011, 2012; STER, 2010a, 2010b, 2012a, 2012b) mean that similar budgets will buy less advertising space and thus reach relatively fewer people or reach them less often. This downward effect will be strongest during the event itself, when advertising rates are highest, and weaker after the event, when rates decrease.

Second, more brands will invest in advertising to try to benefit from the larger audiences. In doing so, brands face fiercer competition for consumers' attention, leading to higher levels of clutter and interference (Burke & Srull, 1988). Competitive clutter, created by advertising messages from competing brands in the same category, can harm own-advertising effectiveness, and especially the number of competing brands has a negative impact on effectiveness (Danaher et al., 2008). In addition, messages from brands from other product categories have a negative impact (Pieters & Bijmolt, 1997). Contextual interference (e.g., Kumar, 2000; Kumar & Krishnan, 2004) coming from brands from different product categories but using similar themes or images is even more harmful because it causes brand confusion (Poiesz & Verhallen, 1989). Brand confusion will be stronger the more advertisers

try to associate themselves with the overall atmosphere and mood, using symbols and colors similar to the specific sport or event (e.g., Keller, 1993).

Similarities in the execution of advertising messages will also have a negative impact on consumers' relative attention because commercials stand out less (Tellis & Ambler, 2007). For advertising to be effective, consumers must pay attention to it (Tellis, 1998). The excitement associated with the event further reduces attention to advertising messages (Newell, Henderson, & Wu, 2001), leading to less elaborate processing (Lee & Sternthal, 1999). Consumers who pay superficial attention to something form only quick impressions and attain short-term memory of it (Haugtvedt, Schumann, Schneier, & Warren, 1994). In addition, as a way to deal with a large number of advertising messages, consumers tend to ignore major parts or even dismiss commercial breaks (e.g., leave the room; Soley, 1984).

The large numbers of advertising messages during sports events are due not only to more brands advertising but also to brands advertising more often. However, the optimal level of exposures is rather low (Vakratsas & Ambler, 1999), with response leveling off relatively quickly afterward. In addition, too frequent exposure may create irritation and negative feelings toward the ad and the brand (Fennis & Bakker, 2001; Pechmann & Stewart, 1990), resulting in lower effectiveness.

Finally, whereas a fit with the experience of the event may increase demand in certain categories, most product categories do not show such fit. Especially in more mature CPG categories, demand is rather stable (e.g., Dekimpe & Hanssens, 1995), and unlikely to be affected by these events. Increases in advertising around the events will consequently not necessarily lead to equally large or even larger additional sales.

2.3. Short- versus long-term effects

Substantial differences exist between short- and long-term sales effects of advertising (e.g., Steenkamp, Nijs, Hanssens, & Dekimpe, 2005). For example, Ataman, Van Heerde, and

Mela (2010) report low short-term effects, with a median elasticity value of 0.008, whereas Srinivasan, Vanhuele, and Pauwels (2010) report significantly higher long-term effects, with a mean elasticity value of 0.036. To account for different evolutions in effectiveness, this study disentangles immediate short-term from cumulative long-term sales effects of advertising.

The effects discussed in previous paragraphs should mainly affect the immediate short-term sales effects of advertising. The cumulative long-term effects, which largely materialize outside (after) event periods, are likely to show more moderate changes. When the event is over, both consumers and brands return relatively quickly to their “normal” behavior. On the one hand, category-demand effects quickly fade (possibly even showing a post-event dip from overstocking), as do the overall positive emotions associated with the event. The high level of competitive interference around the event is likely to lower the *quantity* of processing of the messages, thus reducing the strength of the encoding of the information in consumers’ long-term memory (e.g., Keller, 1993). This, in turn, will lead to stronger forgetting effects and a mitigation of possibly stronger effectiveness due to more people being exposed more often to the advertising messages (Naik, Mantrala, & Sawyer, 1998; Zielske, 1959). On the other hand, as brands return to a normal advertising level, lower levels of competitive interference by new messages make it easier for consumers to remember brands already present in their mind set (Burke & Srull, 1988; Keller, 1993). The association with the event, in turn, may actually promote the encoding of the advertising messages in consumers’ long-term memory, also due to a higher *quality* of processing (Keller, 1993). Both phenomena may (partly) offset possibly lower short-term elasticities caused by higher excitement, more competitive interference and higher advertising rates around the event. Last, the reduction in advertising leads to smaller irritation effects, thus mitigating possible negative effects in the long run. Any (strong) changes should consequently be short lived, leading to more moderate changes in the long-term effects.

Unknown a priori is what factors will have the strongest impact on advertising effectiveness, when they will have such an impact, or what the final outcome will be – namely, increased or reduced advertising effectiveness just before, during, or right after the event relative to periods more distant from the event. Therefore, no specific a priori hypotheses are formulated for the evolution of advertising effectiveness around these events.

3. Methodology

Given the research objectives of this study, several modeling challenges arise. First, this study aims to investigate whether and to what extent advertising elasticities differ around major sports events, and thus the modeling approach should allow advertising effects to differ before, during, and right after an event, relative to periods which are more distant from the event. Second, this study intends to shed light on possibly different evolutions of own-advertising actions versus competitor actions and of immediate versus delayed effects. Therefore, the chosen model should distinguish between own and cross elasticities and between short- and long-term effects. Third, because marketing actions may be driven by their own outcomes, correct estimation of the effects requires accounting for the possible endogeneity of advertising and price decisions. Fourth, the model should be able to handle possible contemporaneous correlations in sales among the brands in a category. Fifth, this study aims to provide generalizable insights across a large variety of brands. Therefore, the model should allow for both individual brand estimates and overall insights.

3.1. Defining timing conditions

To allow for differential effects of advertising investments just before, during, and right after events relative to periods which are more distant from the events, a set of event conditions j is defined. Thus, the often-observed gradual buildup of advertising and media attention to the event and the possible halo effects lasting after the event are covered. The benchmark condition 0 refers to advertising in *outside-event* periods, i.e. periods not covering

the period consisting of two weeks before the event, the week(s) during which the actual event takes place, and two weeks after the event. The *before* condition 1 refers to the two-week period before the event, the *during* condition 2 reflects the week(s) when the actual event takes place, and the *after* condition 3 captures the two-week period after the event.

3.2. Assessing the effectiveness of advertising around major sports events

To assess the impact of advertising on sales, I begin with the well-known error-correction model (e.g., Pauwels, Srinivasan, & Franses, 2007):

$$\begin{aligned}
 \Delta \ln Sales_{bt} = & \beta_{b0} + \sum_{i=1}^I \beta_{bi} M_{it} + \alpha_{b0}^{sr} \Delta \ln Adv_{bt} + \sum_{j=1}^3 \alpha_{bj}^{sr} I_{jt} \Delta \ln Adv_{bt} + \gamma_b^{sr} \Delta \ln Price_{bt} \\
 & + \alpha_{b0}^{sr*} \Delta \ln ComAdv_{bt} + \sum_{j=1}^3 \alpha_{bj}^{sr*} I_{jt} \Delta \ln ComAdv_{bt} + \gamma_b^{sr*} \Delta \ln ComPrice_{bt} \\
 (1) \quad & + \Pi_b \left[\ln Sales_{bt-1} - \left(\begin{aligned} & \alpha_{b0}^{lr} \ln Adv_{bt-1} + \sum_{j=1}^3 \alpha_{bj}^{lr} I_{jt-1} \ln Adv_{bt-1} \\ & + \gamma_b^{lr} \ln Price_{bt-1} \\ & + \alpha_{b0}^{lr*} \ln ComAdv_{bt-1} + \sum_{j=1}^3 \alpha_{bj}^{lr*} I_{jt-1} \ln ComAdv_{bt-1} \\ & + \gamma_b^{lr*} \ln ComPrice_{bt-1} \end{aligned} \right) \right] + \varepsilon_{bt}
 \end{aligned}$$

where

- Δ = first difference operator
- $Sales_{bt}$ = volume sales of brand b in week t
- M_{it} = the vector containing dummy variables for the three conditions, holiday weeks, and quarterly dummies
- I_{jt} = a dummy variable equaling 1 if in condition j (j = 1, 2, 3)
- Adv_{bt} = deflated advertising by brand b in week t
- $Price_{bt}$ = deflated price of brand b in week t
- $ComAdv_{bt}$ = total within-category deflated advertising by competitors of brand b in week t
- $ComPrice_{bt}$ = within-category average deflated price of competitors of brand b in week t
- β_{b0} = the intercept of brand b
- β_{bi} = the main effects of the three conditions, holiday weeks, and quarterly dummies
- α_{b0}^{sr} = the short-term elasticity of advertising by brand b in *outside-event* periods
- α_{bj}^{sr} = change in the short-term elasticity of advertising by brand b in condition j
- α_{b0}^{sr*} = short-term cross-advertising elasticity for brand b in *outside-event* periods

α_{bj}^{sr*}	= change in the short-term cross-advertising elasticity for brand b in condition j
γ_b^{sr}	= short-term price elasticity for brand b
γ_b^{sr*}	= short-term cross-price elasticity for brand b
α_{b0}^{lr}	= long-term elasticity of advertising by brand b in <i>outside-event</i> periods
α_{bj}^{lr}	= change in the long-term elasticity of advertising by brand b in condition j
α_{b0}^{lr*}	= long-term cross-advertising elasticity for brand b in <i>outside-event</i> periods
α_{bj}^{lr*}	= change in the long-term cross-advertising elasticity for brand b in condition j
γ_b^{lr}	= long-term price elasticity for brand b
γ_b^{lr*}	= long-term cross-price elasticity for brand b, and
Π_b	= adjustment effect for brand b

Because sales, advertising, and price are specified in natural logs, effects can be interpreted as elasticities. The terms α_{b0}^{sr} and α_{b0}^{sr*} are the short-term own- and cross-advertising elasticities in *outside-event* periods, respectively, and α_{bj}^{sr} and α_{bj}^{sr*} represent changes in these elasticities around the events.¹ The terms γ_b^{sr} and γ_b^{sr*} are the short-term own- and cross-price elasticities. The terms α_{b0}^{lr} and α_{b0}^{lr*} represent the long-term equilibrium relationship between advertising and sales in *outside-event* periods, where α_{bj}^{lr} and α_{bj}^{lr*} indicate the changes in these equilibriums around the events. Finally, the terms γ_b^{lr} and γ_b^{lr*} represent the long-term equilibrium relationship between own and competitors' prices and sales, respectively. Such equilibrium relationships may occur between cointegrated non-stationary variables, but also between stationary variables (see Van Heerde, Helsen, & Dekimpe, 2007). In the former case, long-term parameters represent permanent effects of permanent changes in the marketing-mix instruments, and in the latter case, they can also refer to the cumulative effects of temporary changes. The term Π_b represents the speed with which the adjustment to long-term equilibrium occurs.

¹ Alternative approaches allowing for time-varying effects exist, including dynamic linear models (Ataman et al., 2010). However, given the large number of brands and periods in the data set, estimating such models would be prohibitive to computing time.

To assess the stationarity of the series, I analyzed the (log-transformed) series at the individual brand level with Phillips and Perron's (1988) test, using an intercept and trend as exogenous variables. In all but 16 (1.6%) of the 206×5 individual series, the unit-root null hypothesis was rejected at the 5% level. However, recent studies have shown that tests based on individual series lack power compared with panel-based unit-root tests. Both Levin, Lin, and Chu's (2002) test and Im, Pesaran, and Shin's (2003) panel unit-root test reject the null hypothesis of a unit root for all five series at the 5% level, thus showing that the data are (trend) stationary. As such, the long-term parameters of the model can be interpreted not only as the permanent effects of permanent changes in the marketing-mix variables but also as the cumulative effects of temporary changes.

3.3. *Endogeneity*

Because advertising and price decisions by brands are possibly endogenous, I use an instrumental variable approach in which the possibly endogenous variables are regressed on the exogenous variables and a set of instruments (Greene, 2003, pp. 397-399). The endogenous variables are $\Delta \ln Adv_{bt}$, $\Delta \ln Price_{bt}$ and the interactions between $\Delta \ln Adv_{bt}$ and the three condition dummy variables. I then replace observed values of the endogenous variables by the predicted values, thus following prior research that has applied this approach to error correction models (e.g., Baghestani, 1991; Boswijk, 1994). To control for possible dependencies of brands from the same category, I allow for a general variance–covariance structure of the error terms of the brands of the same category. The combination of controlling for endogeneity by means of instrumental variables and the subsequent seemingly unrelated regression estimation results in a three-stage least squares estimation with generally lower standard errors for the coefficient estimates (Greene, 2003). A detailed description of the estimation procedure can be found in appendix.

As instrumental variables, I use both the first differenced and the lagged advertising and price variables from *other product classes* (Lamey, Deleersnyder, Steenkamp, & Dekimpe, 2012; Van Heerde, Gijsenberg, Dekimpe, & Steenkamp, 2013); specifically, I distinguish among food, beverages, personal care, and household care. Thus, for a food brand, both the first differenced and the lagged log advertising and log price (separately) for beverages, personal care, and household care serve as instruments. Advertising and price changes for other product classes may be due to the same underlying cost structures (Van Heerde et al., 2013). However, these structures are likely to be unrelated to demand shocks in the focal product class.

Because I instrument for the first differences of advertising and price, as well as for the interactions of the first difference of advertising with the three condition dummy variables, I also include the interactions between the original instruments and the condition dummy variables in the instrumental variable equations (Wooldridge, 2002, pp. 121-122). The resulting instrumental variable equation is shown in equation 2. Each endogenous variable Y_{ebt} is thus regressed on the exogenous variables from equation 1 and the instruments introduced previously. Because the instruments outnumber the endogenous regressors, the model is over-identified.

$$\begin{aligned}
 Y_{ebt} = & \varphi_{eb0} + \sum_{i=1}^I \varphi_{ebi} M_{it} + \lambda_{eb0}^{sr*} \Delta \ln \text{ComAdv}_{bt} + \sum_{j=1}^3 \lambda_{ebj}^{sr*} I_{jt} \Delta \ln \text{ComAdv}_{bt} + \omega_{eb}^{sr*} \Delta \ln \text{ComPrice}_{bt} \\
 & + \sum_{c=1}^3 \left[\begin{aligned} & \lambda_{ebc0}^{sr} \Delta \ln \text{Adv}_{ct} + \sum_{j=1}^3 \lambda_{ebcj}^{sr} I_{jt} \Delta \ln \text{Adv}_{ct} \\ & + \omega_{ebc0}^{sr} \Delta \ln \text{Price}_{ct} + \sum_{j=1}^3 \omega_{ebcj}^{sr} I_{jt} \Delta \ln \text{Price}_{ct} \end{aligned} \right] \\
 (2) \quad & + \Pi_{eb}^{IV} \left[Y_{ebt-1} - \left(\begin{aligned} & \zeta_{eb0}^{lr} \ln \text{Adv}_{bt-1} + \sum_{j=1}^3 \zeta_{ebj}^{lr} I_{jt-1} \ln \text{Adv}_{bt-1} + \psi_{eb}^{lr} \ln \text{Price}_{bt-1} \\ & + \lambda_{eb0}^{lr*} \ln \text{ComAdv}_{bt-1} + \sum_{j=1}^3 \lambda_{ebj}^{lr*} I_{jt-1} \ln \text{ComAdv}_{bt-1} \\ & + \omega_{eb}^{lr*} \ln \text{ComPrice}_{bt-1} \\ & + \sum_{c=1}^3 \left[\begin{aligned} & \lambda_{ebc0}^{lr} \ln \text{Adv}_{ct-1} + \sum_{j=1}^3 \lambda_{ebcj}^{lr} I_{jt-1} \ln \text{Adv}_{ct-1} \\ & + \omega_{ebc0}^{lr} \ln \text{Price}_{ct-1} + \sum_{j=1}^3 \omega_{ebcj}^{lr} I_{jt-1} \ln \text{Price}_{ct-1} \end{aligned} \right] \end{aligned} \right) \right] + v_{ebt}
 \end{aligned}$$

To assess the quality of the instruments, I test for their strength and validity using the Angrist–Pischke multivariate F test (Angrist & Pischke, 2009) and the Sargan test (Sargan, 1958), respectively. These tests show that the instruments are sufficiently strong (p -value of the F tests < 0.05) and that they are not correlated with the error term of the main equation ε_{bt} (p -value of the Sargan test > 0.05).

3.4. Exploring heterogeneity

Effects both across all brands and across specific subsets of brands can be evaluated by means of the added Z method (Rosenthal, 1991)². I first analyze the overall elasticity evolution and subsequently I explore the elasticity evolution of (1) brands that do not increase their SOV around sports events through additional advertising investments versus those that do so around single-sport events and multi-sports events; and (2) products that show a fit with the event versus those that do not.

Single-sport events are events that focus on only one sport (e.g., FIFA World Cup), and multi-sports events cover multiple sports (e.g., the Olympics). I subsequently compared the included brands' average advertising investments in the benchmark (outside-event) condition with their average investments in the three event conditions, thereby distinguishing between their behavior around single-sport and multi-sports events. When the brands increased their advertising investments, I analyzed the resulting change in SOV. To test whether these increases in advertising also resulted in significant changes in SOV, the latter were judged at the 5% significance level (one-sided). In the single case in which SOV significantly increased around both single- and multi-sports events, the most significant increase (i.e., single-sport event) was selected.

Three independent expert judges determined product fit with the event, judging the fit along two dimensions: whether the product shows a “functional fit” (e.g., Gwinner & Eaton,

² For recent applications of this method in marketing, see Kremer, Bijmolt, Leeflang, & Wieringa (2008), Lamey et al. (2012), and Van Heerde et al. (2013).

1999) or an “experience fit” (e.g., McDaniel, 1999) with sports events. All three judges agreed in 75% of the cases, and in the other 25%, the majority judgment was followed. Typical categories showing such event fit include shower gels, deodorant, beer, savory snacks, and soft drinks.

4. Data description

The proposed model is estimated on weekly information from 2002 through 2005 for 64 consumer packaged goods (CPG) categories in the United Kingdom. The data cover a wide range of food, beverages, personal care, and household care products and thus provide a good sample of the assortment offered in a typical supermarket. In total, 206 brands were included in the analyses. Table 1 provides an overview of these product classes, together with the number of categories in these classes and illustrative example brands for several categories.

-- Insert Table 1 about here --

Advertising data come from NielsenMedia and are aggregated across television, radio, print, direct mail, outdoor and cinema advertising. Brands included in the analyses are all national brands, because private labels are typically not advertised individually (Lamey et al., 2012). All brands were available in the market for the full four years and show advertising actions in at least eight weeks in each of the conditions.³ Information on volume sales and prices come from Kantar Worldpanel UK. This information is based on data aggregated across its consumer panel of more than 17,000 British households that, on a daily basis, scan their fast-moving consumer goods purchases across all retail channels.⁴

Competitor advertising and price are determined as total advertising by all other brands in the same category (e.g., breakfast cereals, soft drinks) and average price across

³ This advertising activity threshold was selected to obtain reliable estimates of the three event-related condition effects. The included brands are typically larger and more advertising intensive than those that did not meet the threshold, with average market share of 9.8% (5.2%), average advertising frequency of 59.0% (9.0%), and average advertising investment of £131,298 (£59,733). The included brands account for 83.6% (81.0%) of advertising expenditures in general (*around the events*), thus providing a good indication of the general evolution of advertising effectiveness.

⁴ I gratefully thank AiMark for providing the data.

these brands, respectively. To account for the full competitive environment, information of *all* other brands active in the category was included, regardless of whether these brands met the advertising activity threshold.

Table 2 presents the major sports events considered. The selection is based on sports events generating the most attention from both British media and the general public. Each event is categorized as either a single-sport or multi-sports event, depending on whether it covers only one or multiple sports. Analyzing multiple events helps overcome any idiosyncrasies associated with one specific (possibly returning) event.

-- Insert Table 2 about here --

5. Model-free insights

5.1. General descriptive insights

Table 3 presents summary statistics on the brands' market shares, advertising frequency, and average advertising investment. Although this study includes only brands from mature CPG categories on the market for the full four years, considerable variability exists in the average market shares and advertising behavior of the brands. Advertising frequency is the highest among household care products and the lowest among food products. Conversely, the latter show considerably higher expenditures per advertising activity, especially when compared with beverages. As such, this study includes both small and large brands and both less frequent and more frequent advertisers, with advertising frequencies ranging from a low of 15% of the time to a high of full-time advertising.

-- Insert Table 3 about here --

5.2. Advertising behavior around events

Table 4 provides insights into the evolution of the brands' advertising behavior. The table compares brands' behavior before, during, and after the event with their behavior in outside-event periods. Data limitations prevent distinguishing the level of internal reference to

the event, only the timing of the advertising efforts. Table 4 shows that these events attract strong additional advertising investments, with increases of around 25% in all three periods. It also shows that, in general, this increase is due to an increase in both the number of advertisers and the average advertising investment, with advertising brands spending up to 11% more during the event⁵.

-- Insert Table 4 about here --

5.3. Advertising and sales evolution

Fig. 1 shows whether these increases in advertising correspond with equally strong or stronger increases in sales. The dotted black line shows the overall advertising expenditures evolution. The evolution appears as an index relative to the average level over the whole period. The full dark gray line shows the volume sales evolution. Because volume units are different for different types of products (e.g., grams for food, liters for beverages), sales evolutions were indexed on a brand-per-brand basis, after which the median per week is reported. With the median, the results are less affected by extreme index evolutions of smaller brands. Finally, gray zones represent the combined *before*, *during*, and *after* conditions, and white zones represent the *outside-event* condition.

-- Insert Figure 1 about here --

Fig. 1 shows the strong variability in advertising expenditures, with alternations between weeks with high spending and weeks with low spending. However, overall, both the overall level of advertising and the spikes are higher in the gray event-related zones than in the white *outside-event* zones, confirming the findings in Table 4. Whereas advertising expenditures are volatile over time and clearly show increases around the events, sales are

⁵ All classes experience a considerable increase in the number of brands advertising around these events. Average advertising investments show strong increases in the beverages and personal care classes, but they diminish in the food class both *during* and *after* the event. Therefore, mainly beverages and personal care benefit from increased advertising spending around these events. Typical brands showing higher average advertising spending include Doritos (ambient dips), Gillette (razor blades), and Heineken (beer). Brands reducing their average advertising efforts include Aquafresh (toothbrushes), Cif (household cleaner), and Flora (margarine).

relatively stable, with seasonal increases toward the end of the year, followed by a strong drop. As such, the strong increases in advertising around the events do not seem to be associated with strong increases in sales, suggesting a decrease in advertising effectiveness.

6. Model-based insights

6.1. Model diagnostics

Before discussing the results of the analysis, I first offer insights into the quality of the model. Although the error correction specification defined in Eq. (1) allows for the straightforward disentanglement of short- versus long-term effects, current changes in sales may still be directly influenced by past changes in both own and competitor marketing actions. Therefore, in addition to the current changes in marketing actions, I added up to three lagged changes to the model (Wickens & Breusch, 1988). A final rival model assumed a one-period delayed effect of advertising instead of an immediate effect. The analyses show that the base model is the preferred specification because it has the lowest Akaike information criterion (-2.338 vs. -2.324 , -2.311 , -2.304 , and -2.326 , respectively) and Bayesian information criterion (-1.868 vs. -1.787 , -1.707 , -1.633 , and -1.857 , respectively). As a consequence, only current changes in marketing actions appear in the final model.

The overall performance of the model is first of all judged by the R-square, root mean squared error (RMSE) and geometric mean of the relative absolute error (GMRAE)⁶. Overall, from the full four-year sample, the model fit is good, with an average R-square of 0.395. The average RMSE for the full sample is 0.323 and the average GMRAE equals 0.524, which is considerably lower than 1. To judge the relative in-sample versus out-of-sample performance of the model, the sample was subsequently split in a three-year estimation sample and a one-year holdout sample. Following Brodie and De Kluyver (1987), I include *observed* competitors' actions. This split-sample analysis confirms the good forecasting performance,

⁶ As the dependent variable series, which consist of first differences of the log-transformed volume sales, are characterized by both many values near zero and considerable fluctuations, I follow the recommendations by Armstrong (2001, p.277) and use relative error measures not expressed in percentages.

with the average RMSE and GMRAE equaling 0.311 and 0.510 (in-sample), and 0.414 and 0.742 (out-of-sample), respectively. Although both the RMSE and GMRAE increase out-of-sample, increases are acceptable and resultant values are still low.

The predicted first differences in the sales series allow for the construction of the associated predicted level series, and subsequent comparison to the observed level series. The predicted level series are based on a static forecast. This forecast does not allow for weekly updating with new information on the *observed* sales level in previous period, but instead uses the *predicted* level in previous period. As such, this is a more rigid test of the forecasting ability of the model, with errors increasing over time. The average (*median*) mean absolute percentage error (MAPE) is 0.182 (*0.103*) for the full four-year sample. The split-sample analysis results in a good in-sample MAPE of 0.144 (*0.091*) and a reasonable out-of-sample MAPE of 0.359 (*0.190*). Fig. 2 shows the out-of-sample forecasting performance based on the level series. Similar to Fig. 1, indexed sales evolutions were calculated for panel A. The full dark gray line shows the actual evolution over time, and the dotted black line shows the predicted evolution. Panel B depicts the sales levels for the brand with the median out-of-sample MAPE. Here as well, the full dark gray line shows the actual evolution over time, and the dotted black line shows the predicted evolution. The thin black line represents the absolute percentage error evolution. Both panels provide evidence of the reasonably good out-of-sample predictive performance of the model.

-- Insert Figure 2 about here --

6.2. Model results

6.2.1. The effects of major sports events on sales

Table 5 shows the overall across-brand parameter estimates, together with the associated added Z-scores (Rosenthal, 1991). Major sports events have a positive impact on the sales of these mature CPG categories, with a slight increase in sales *before* the event ($\bar{\beta}_1 =$

0.010) and the strongest impact *during* the event ($\bar{\beta}_2 = 0.012$). These findings confirm reports by research agencies and business press of the positive effects of such events on supermarket sales (e.g., ING, 2012).

-- Insert Table 5 about here --

6.2.2. Own-advertising effectiveness around major sports events

Short-term own-advertising elasticities ($\bar{\alpha}_0^{sr} = 0.009$) experience a strong negative impact of major sports events *before* ($\bar{\alpha}_1^{sr} = -0.004$), *during* ($\bar{\alpha}_2^{sr} = -0.006$), and *after* ($\bar{\alpha}_3^{sr} = -0.004$) the event. As such, advertising investments have, on average, more than 50% less direct impact on the sales of brands around these events, with the strongest reduction during the event itself. Advertising rates, clutter and the excitement associated with the event all reach their peak and seem to outweigh the positive effects of the larger audience and the transfer of positive feelings, resulting in the strongest reduction in effectiveness. Though small, the reported elasticities are in line with the findings of Allenby and Hanssens (2004), who show that advertising elasticities for established products are approximately 0.01, and Ataman et al. (2010), who report a median value of 0.008. In addition, in their meta-analysis, Sethuraman, Tellis, and Briesch (2011) find that more than half the analyzed advertising elasticities had values between 0 and 0.1 and that only about half the included elasticities were significantly greater than 0.

The results also show a significant, negative effect of the events on long-term own-advertising elasticities, though the pattern differs from the short-term elasticities. Compared with *outside-event* periods ($\bar{\alpha}_0^{lr} = 0.014$), elasticities significantly decreased both *before* ($\bar{\alpha}_1^{lr} = -0.007$) and *during* ($\bar{\alpha}_2^{lr} = -0.006$) the event but did not significantly change *after* the event. Long-term elasticities represent the cumulative effect of a one-time change in advertising on sales in the subsequent weeks after the advertising action. As such, the long-term elasticities of advertising *before* and *during* the event are still negatively affected by the clutter and

excitement associated with the event which interfere with consumers' long-term memory. However, part of the strong drop in the short-term elasticity *during* the event will be offset by the beneficial influence of the link between the brand and the event which promotes the encoding in the long-term memory (Keller, 1993). The long-term elasticity of advertising *after* the event experiences a much smaller negative impact of clutter and excitement, whereas it can still somewhat benefit from this link between the brand and the event (Keller, 1993).

As mentioned, the negative evolution of both short- and long-term elasticities could partly be driven by higher advertising rates. Section 6.5.1 discusses a simulation study which suggests that the relative impact of higher advertising rates on this evolution is limited.

6.2.3. Competitors' advertising effectiveness around major sports events

To obtain a full picture of advertising effectiveness around major sports events, I also investigated the impact on advertising cross-elasticities, that is, the impact of advertising by competitors on the sales of the focal brands. Cross-elasticities are positive, both in the short run ($\bar{\alpha}_0^{sr*} = 0.006$) and the long run ($\bar{\alpha}_0^{lr*} = 0.012$). These positive category-demand effects are in line with the findings of Schultz and Wittink (1976), Lancaster (1984) and Van Heerde et al. (2013). According to the typology of Schultz and Wittink (1976), this situation can be considered a 'Case IV' in which advertising by one brand positively affects the sales of all brands in the category, but has a stronger effect on the advertising brand. As such, advertising by any brand in the category can be considered a reminder to consumers to replenish their stocks. At the same time, this finding shows strong resemblance to category-demand effects of price promotions (see Nijs, Dekimpe, Steenkamp, & Hanssens, 2001).

These positive cross-elasticities, however, are also affected by the events. Short-term elasticities are significantly reduced *before* ($\bar{\alpha}_1^{sr*} = -0.005$), *during* ($\bar{\alpha}_2^{sr*} = -0.004$), and *after* ($\bar{\alpha}_3^{sr*} = -0.004$) the event, whereas long-term elasticities only significantly decrease *before*

($\bar{\alpha}_1^{lr*} = -0.009$) and *during* ($\bar{\alpha}_2^{lr*} = -0.006$) the event. Thus, cross-elasticities show a similar pattern to own-advertising elasticities, and the same factors are likely to affect this pattern.

6.3. Advertising elasticity evolution around major sports events

Using the individual-brand estimates, I calculated the brand-specific elasticities for the benchmark condition of *outside-event* periods and the three event conditions, together with the associated standard deviations. I subsequently repeated the added Z analysis on these elasticities. Fig. 3 depicts the results. The figure shows the clear drop in short-term own-advertising elasticities, reaching a low of 0.002 (a decrease of more than 75%) *during* the event itself. Long-term own-advertising elasticities suffer somewhat less, with a decrease of nearly 45% *before* and *during* the event to values of approximately 0.008; the elasticity *after* the event (0.013) is not significantly different from *outside-event* periods (0.014). As such, the immediate impact of own-advertising investments is the most harmed, whereas the long-term effectiveness of advertising after the event is not significantly altered.

-- Insert Figure 3 about here --

Both short- and long-term cross-advertising elasticities are insignificant *before* the event. Here as well, short-term elasticities are highest *after* the event (0.003), but in the long run (0.010), they are not significantly different from *outside-event* periods (0.012).⁷

Combining these results, it can be concluded that when it comes to immediate effects of advertising, brands suffer the most in the weeks *before* and *during* the event, whereas the negative effects are somewhat mitigated *after* the event. In the long run, the negative effects are strongest *before* the event. In contrast, advertising around the event is most effective

⁷ All product classes show the negative impact on the associated advertising elasticities. Food products face strong reductions in both short- and long-term own effectiveness, up to -90% *during* the event itself. Own-advertising elasticities for beverages are reduced with 70% (*during*) in the short run and 47% (*before*) in the long run. Personal care products face insignificant short-term own effectiveness *during* the event itself, whereas reductions in long-term own-advertising elasticities are fairly limited (-36% *before* but only -15% *during* the event). Finally, household care products show relatively moderate decreases in long-term own effectiveness *before* (-36%) and *during* (-13%) the event. Remarkably, own advertising for these products is most effective *after* the event, in both the short and the long run (both +25%).

during the weeks *after* the event, when brands do not suffer from significant reductions in effectiveness compared with *outside-event* periods.

6.4. Increased SOV as a strategy to counter diminished advertising effectiveness

The downward evolution of advertising effectiveness questions the soundness of increasing investments in advertising around these events. More particularly, it raises questions on the extent to which evolutions may differ for brands that not just invest somewhat more in advertising but raise their advertising so much that they are able to significantly increase their SOV. These brands, on average, have similar market shares (10.3% vs. 9.6%) but lower overall SOV and average advertising expenditure levels (−7% and −18%, respectively) than brands not increasing their SOV. In addition, these brands are positioned at the higher end of the price spectrum, with price ratios relative to their competitors being 9% higher than brands not increasing their SOV. As such, these brands can be categorized as “premium niche” brands (Van Heerde et al., 2013).

The subsequent analysis distinguishes between brands that increase their SOV predominantly around multi-sports events (e.g., the Olympics) and those that increase their SOV predominantly around single-sport events (e.g., FIFA World Cup). These two types of events differ in their contact possibilities with audiences in two dimensions: reach and frequency. Whereas the former reaches a wide audience, frequency of contact (number of exposures) may be more limited. Conversely, the latter type may reach a somewhat narrower audience, but the number of exposures may be higher. The results appear in Fig. 4. For a more concise discussion, focus is on the actionable instrument, own advertising.

-- Insert Figure 4 about here --

Panel A shows the clear reduction in short-term own advertising elasticities of brands that do not significantly increase their SOV by means of additional advertising investments. It also shows that investing heavily around multi-sports events, characterized by relatively

scattered audiences, does not pay off in the short run. Meanwhile, brands investing heavily around single-sport events, with more focused audiences, benefit from higher advertising elasticities *before* and *after* the event (+20% and +60%, respectively). However, *during* the events themselves, elasticities drop dramatically, even becoming insignificant.

For the long-term effectiveness of advertising, panel B shows the general pattern for both the brands that do not significantly increase their SOV and the brands that focus on multi-sports events. In contrast, brands focusing on single-sport events show increases in elasticities of approximately 50% *after* the event. Long-term effects of advertising *during* the event remain more or less the same, indicating that advertising during the event may not have an immediate impact on sales but certainly does no harm in the long run.

However, SOV is a relative measure; it is affected not only by own-advertising investments but also by those of competitors.⁸ In the short run, a strategy of increasing advertising expenditures around single-sport events even more than the competition is the most rewarding strategy, with short-term elasticities doubling *before* and *after* the event (0.009 and 0.010 compared with 0.005, respectively), but becoming insignificant *during* the event. Of note, brands that combined increased own investments with decreasing competitor activity showed similar advertising elasticity evolutions for both types of events, with the strongest reductions *before* the event (−78% and −71%, respectively) but no significant change *after* the event. Regarding the long run, brands increasing their SOV around multi-sports events clearly do better when own increases in advertising are even stronger than increases in advertising by competitors, as the elasticity remains relatively constant, only becoming insignificant *before* the event. However, brands that increase their SOV around single-sport events as a result of increased own and decreased competitor advertising are the

⁸ Of the brands increasing their advertising and showing increased SOV around multi-sports (single-sport) events, 41% (69%) showed stronger increases in expenditures than their competitors, while 59% (31%) combined increased own advertising with decreased competitor advertising. Only five brands were able to significantly increase their SOV as a consequence of reduced competitor advertising without increasing their own-advertising investments. As such, this number of brands is too small to provide generalizable insights.

true winners, with elasticities increasing from 0.012 *outside-event* periods to 0.019 *during* and 0.021 *after* the event.

6.5. Additional insights

6.5.1. The role of advertising costs

The results reported previously pertain to advertising investments expressed in monetary terms. A simulation could shed light on the extent to which the reported decreases in advertising effectiveness depend on increases in advertising cost. In this what-if simulation, the proposed model was re-estimated, using cost-adjusted advertising expenditures. The benchmark case is the model reported previously, in which one monetary unit represents one advertising unit. Advertising rates around such sports events are reported to show markups of 5-15%, on average, with a high of 40%⁹, which is considerably lower than the extreme increases around the Super Bowl. Unit advertising costs were hence hypothesized to show a) fixed increases of 25% and 50% around all events, and b) dynamic increases of 5-15% and 10-30% across the events. As a result of the increased costs, the same monetary unit would then buy only a) 0.80 and 0.67 advertising units, and b) 0.95-0.87 and 0.91-0.77 advertising units, respectively. Table 6 shows the results of the simulation.

-- Insert table 6 about here --

Increases in unit advertising costs appear to have only limited impact on advertising elasticities. Fixed adjustments are largely absorbed by stronger main effects of the different conditions after the log-transformation of the advertising variables. Dynamic adjustments show a similar result. This may be a consequence of the rather small variation in the adjustments (making them almost a fixed adjustment), combined with relatively small changes in price levels. As such, reductions in advertising elasticities around the events seem to be driven not so much by increases in advertising cost as by clutter and other phenomena.

⁹ I use data from STER, the Dutch public broadcasting advertising agency, as proxy for the situation in the UK. As Steenkamp et al. (2005) show that the Netherlands and the UK resemble each other well on a number of key marketing (advertising) statistics, we may expect that the relative advertising cost evolutions are also similar.

6.5.2. *Fit with the event*

It could be argued that product categories that show a fit with this type of event experience vastly different evolutions in advertising effectiveness relative to those that do not. Fig. 5 shows that in the short run, advertising elasticity evolutions of event-fit categories are not different from the overall pattern. *During* the event itself, advertising, on average, will not even have a significant immediate effect. This may be an indication of the relative over-spending that takes place in these categories. However, these categories suffer less *before* and *after* the event than non-event-fit categories (reductions of 22% vs. 50% and 63%, respectively). Long-term elasticities of event-fit categories also follow the general pattern, with decreases *before* and *during* the event and recovery *after* the event.

-- Insert Figure 5 about here --

6.5.3. *The effectiveness of price promotions around major sports events*

Major sports events not only attract additional spending on advertising but also increased investments in price promotions (Keller, Deleersnyder, & Gedenk, 2013). It would consequently be useful to determine whether the effectiveness of brands' own-price promotions also changes around these events¹⁰. Expanding the model with the interactions of own price (first differenced and lagged version) with the three condition dummies showed that this indeed is the case. Short-term own-price elasticities more than doubled, from -0.358 *outside-event* periods to -0.827 (*before*), -0.748 (*during*), and -0.623 (*after* the event). Long-term elasticities also become stronger, but to a lesser extent, from -0.480 *outside-event* periods to -0.673 (*before*), -0.644 (*during*), and -0.584 (*after* the event). These results indicate that part of the immediate increase in sales is subsequently offset by a post-promotion dip (see Van Heerde, Leeflang, & Wittink, 2000). These findings, which are in line with Keller et al.'s (2013) results, show that whereas advertising becomes less appealing around

¹⁰ I thank an anonymous reviewer for this suggestion.

major sports events, investments in price reductions can be a rewarding strategy for brands, especially in the short run.

7. Discussion

7.1. Summary

Notwithstanding the enormous advertising investments around major sports events, no study has systematically investigated when advertising effectiveness is highest around these events. This study therefore aims to provide insights into the extent to which advertising elasticities are different just before, during, and right after the events, compared with periods more distant from the event. It does so by analyzing the evolution in the advertising elasticities for 206 brands from 64 mature CPG categories covering a period of four years of weekly data around a set of sports events that receive the strongest coverage by UK media. In addition, this study examines the extent to which it pays off to invest heavily so as to increase the brand's SOV around these events.

The data confirm anecdotal evidence that these events indeed cause surges in advertising, with both the number of advertising brands going up (+7%) and the average amount spent on advertising increasing (+10%, on average). This is a clear indication of the perceived utility among managers of boosting advertising around these events to reach larger audiences in shorter periods, while benefiting from the overall positive mood these events engender.

Contrary to these expectations, this study shows that brands' advertising effectiveness strongly diminishes around these events, with especially the short-term elasticities showing a strong decline. Brands suffer from the clutter caused by the increased number of advertising messages, from both the same (Danaher et al., 2008) and other (Pieters & Bijmolt, 1997) categories, competing to capture consumers' attention, with a peak during the event period itself. Effectiveness further declines during the event period as the excitement associated with

the event reaches its peak, with lower attention to advertising messages (Newell et al., 2001). In addition, as sales in these mature categories are relatively stable over time, strong increases in advertising are not followed by equally strong or even stronger increases in sales. The role of higher advertising rates in the decline of advertising elasticities is suggested to be limited.

Whereas brands experience a strong reduction of the immediate sales effects of their advertising investments, long-term cumulative effects, as expressed in long-term advertising elasticities, show a somewhat smaller decline. Long-term elasticities are smallest before the event. The event itself and the excitement created by it are likely to interfere with the memory nodes of brands associating themselves with the event (e.g., Keller, 1993). During the event, strong increases in advertising activity will dramatically reduce short-term elasticities. Long-term elasticities, on the other hand, benefit from the link between the brand and the event which promotes the encoding in the long-term memory (Keller, 1993), thus partly offsetting the drop in the short-term elasticities. An important corollary of this is the fact that, during major sports events, the old 'long run = 2 times short run' rule of thumb concerning advertising elasticity ratios clearly no longer holds. During major sports events, long-term own-advertising elasticities are up to 4 times higher than their short-term equivalents.

Brands, however, not only suffer from reduced own-advertising elasticities around the events; positive category demand effects (e.g., Schultz & Wittink, 1976; Van Heerde et al., 2007) also decline, especially in the short run. In turn, long-term effects show similar patterns to own-advertising elasticities. Here as well, the impact of higher advertising rates appears limited. These findings indicate that brands benefit less from investments in advertising around major sports events, regardless of whether these are own or competitors' investments.

A possible way to escape from this negative effectiveness evolution is to increase advertising spending in such a way that it results in significant increases in SOV around

single-sport events. Whereas short-term effects become insignificant during the event, long-term effects remain stable and significantly increase in the weeks right after the event.

7.2. Managerial implications

Many brands are attracted by major sports events to engage in advertising. The observed behavior is twofold, with more brands advertising around these events while spending more on individual actions. However, the results of this study show that such herding behavior (“I must advertise because everybody else is doing so”) may not be an optimal strategy, at least when the brands’ focus is on directly increasing sales through advertising. Although the long-term sales effects are also smaller around the events, especially the immediate effects decline, rendering advertising a much less effective tactical instrument to boost sales in the short run and thus reducing its attractiveness as a marketing-mix instrument.

Traditional marketing-mix optimization rules (e.g., Dorfman & Steiner, 1954) recommend shifting budgets to marketing instruments that are relatively more effective in increasing sales (e.g., loyalty actions with non-financial incentives linked to the event; Minnema, Non, & Bijmolt, 2012). The observation that short-term price elasticities become more effective around these events suggests shifting advertising budgets especially to price discounts. Advertising efforts, in turn, could best be aimed at normal, outside-event periods, when brands will receive much more “bang” for their “buck.” This, however, does not mean that advertising budgets should necessarily be at zero, as advertising can serve as a catalyst for other marketing instruments (Naik, 2007) while being ineffective itself.

If sufficient funds are available, brands can still use these events to increase their sales by additional advertising investments. Two conditions apply: (1) investments should be focused on single-sport events, and (2) they should not be simple incremental investments but profound increases resulting in a significant lift of the brand’s SOV. By focusing on single-

sport events (e.g. FIFA World Cup), brands will have better chances of reaching a more focused group of consumers multiple times. By outspending competitors, they will be able to stand out from the clutter and to gain more attention from consumers. In turn, this will increase the likelihood of purchase.

Even when budgets do not allow for such increase in SOV, increasing advertising around major sports events is not necessarily without value. Firms often use event-related marketing activities to improve brand awareness and brand image and, thus, to build brand equity in the long run (Keller, 2007). These activities help positioning the brand relative to its competitors. By (implicitly) associating the brand with the event, brands can still benefit from the transfer of positive feelings and emotions associated with the event to their brands (Grohs et al., 2004) and thus improve their brand image (e.g., De Pelsmacker, Geuens, & Anckaert, 2002; Keller, 2007). Furthermore, if there is a clear fit between the values associated with the event and those proposed by the brand, advertising around the event can strengthen the brand image and positioning even further, an example of so-called match-up effects (McDaniel, 1999). As such, it shows resemblance to direct sponsoring of events (Parker, 1991): the better the fit between the event and the brand, the more useful is additional advertising to build brand equity in the long run.

7.3. Limitations and future research directions

In this study, advertising investments were measured in monetary terms. However, these data may mask changes in media rates, with the same budget buying less advertising space in certain periods of the year (e.g., around sports events). Further research on the effect of such changes on advertising effectiveness, using actual (not proxy) media rates, is warranted.

Second, this study focused on advertising investments and did not include other event-related marketing activities of brands (e.g., Minnema et al., 2012). Advertising around the

event could then mostly assume a role as catalyst, thus reinforcing the effects of the other activities rather than showing increased own sales effectiveness (e.g., Naik and Raman, 2003; Raman and Naik, 2004).

Third, the analyses focused only on advertising elasticities. Investigating the extent to which advertising messages are generic or more tailored to the specific event could provide additional insights into the extent to which evolutions are caused by a fit between the advertising and the event.

Fourth, although this study confirms that price promotions become more effective around events (see also Keller et al., 2013), uncovering the reasons behind this evolution and understanding the possible interplay with price-oriented and/or event-associated advertising in an integrated marketing strategy would be a promising research avenue.

Finally, this research was deliberately limited to surges in normal advertising by CPG brands. Except for some notable exceptions, such as Coca-Cola, Budweiser, and Carlsberg, such brands are seldom official sponsors of major sports events. Although it would be conceptually important to investigate the link between official sponsorship and advertising effectiveness, this would likely require the extension of the research to durables.

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Table 1

Overview of included product categories.

Product Class	Number of Categories	Example Categories	Example Brands
Food	22	Breakfast cereals Savory snacks Yoghurt	Kellogg's Pringles Danone
Beverages	17	Lager Mineral water Softdrinks	Heineken Evian Coca-Cola
Personal care	15	Cleansers Dentifrice Shampoo	Oil of Olay Colgate L'Oreal
Household care	10	Household cleaners Liquid detergents Machine wash products	Flash Fairy Ariel
Total number	64		206

Table 2

Overview of included sports events.

Event	Period	Event Type
2002 Winter Olympic Games	8-24 February 2002	Multi-sports
2002 FIFA World Cup	31 May-30 June 2002	Single-sport
2002 Commonwealth Games	25 July-4 August 2002	Multi-sports
2003 ICC Cricket World Cup	9 February-24 March 2003	Single-sport
2003 IRB Rugby World Cup	10 October-22 November 2003	Single-sport
2004 UEFA European Football Championship	12 June-4 July 2004	Single-sport
2004 Summer Olympic Games	13-29 August 2004	Multi-sports
FA Cup Final	4 May 2002	Single-sport
	17 May 2003	
	22 May 2004	
	21 May 2005	
AELTC Championships Wimbledon	24 June-7 July 2002	Single-sport
	23 June-6 July 2003	
	21 June-4 July 2004	
	20 June-3 July 2005	

Table 3

General descriptives.

Product Class	Market Share	Advertising Frequency (percentage of weeks with advertising)	Average Advertising Investment (when investing)
Overall	9.8% (10.7)	59.0% (22.8)	£131,298 (192,061)
Food	12.4% (10.4)	51.0% (19.1)	£141,269 (222,656)
Beverages	8.6% (12.5)	63.2% (23.3)	£115,421 (177,651)
Personal care	7.9% (8.8)	56.0% (22.9)	£138,547 (181,876)
Household care	11.8% (9.6)	67.1% (22.6)	£139,369 (194,644)

Note. The first line in each product class represents the averages across brands within the specific product class. The second line, with values between brackets, represents the standard deviations across the same brands.

Table 4

Overall advertising behavior.

Product Class	Average Total Advertising (per week)	Average Percentage of Advertising Brands (per week)	Average Advertising Investment (when investing)
Overall			
Outside event	£14,478,939	56%	£125,587
Before event	£17,956,152 (+24%)	63%	£138,740 (+10%)
During event	£18,263,986 (+26%)	63%	£139,924 (+11%)
After event	£18,084,676 (+25%)	64%	£137,104 (+ 9%)
Food			
Outside event	£ 3,350,149	49%	£143,248
Before event	£ 3,700,525 (+10%)	54%	£143,817 (+ 0%)
During event	£ 3,599,420 (+ 7%)	55%	£136,113 (- 5%)
After event	£ 3,538,805 (+ 6%)	54%	£136,608 (- 5%)
Beverages			
Outside event	£ 4,266,055	60%	£107,715
Before event	£ 5,658,836 (+33%)	68%	£125,967 (+17%)
During event	£ 5,710,149 (+34%)	68%	£127,049 (+18%)
After event	£ 5,480,633 (+28%)	68%	£122,570 (+14%)
Personal Care			
Outside event	£ 4,027,280	52%	£130,251
Before event	£ 4,994,313 (+24%)	60%	£140,381 (+ 8%)
During event	£ 5,550,584 (+38%)	61%	£154,302 (+18%)
After event	£ 5,667,676 (+41%)	64%	£150,851 (+16%)
Household Care			
Outside event	£ 2,835,455	65%	£132,628
Before event	£ 3,602,479 (+27%)	70%	£155,331 (+17%)
During event	£ 3,403,833 (+20%)	70%	£146,982 (+11%)
After event	£ 3,397,564 (+20%)	72%	£143,271 (+ 8%)

Table 5

Overall across-brand parameter estimates.

		Expected sign	Weighted beta	Z-score
Intercept	$\bar{\beta}_0$	$\neq 0$	0.007 ***	2.538
<i>x Before Event</i>	$\bar{\beta}_1$	$\neq 0$	0.010 **	2.277
<i>x Event</i>	$\bar{\beta}_2$	$\neq 0$	0.012 ***	3.128
<i>x After Event</i>	$\bar{\beta}_3$	$\neq 0$	0.006	1.433
Holiday	$\bar{\beta}_4$	$\neq 0$	-0.007	-1.407
Qtr1	$\bar{\beta}_5$	$\neq 0$	-0.016 ***	-3.778
Qtr2	$\bar{\beta}_6$	$\neq 0$	-0.019 ***	-4.026
Qtr3	$\bar{\beta}_7$	$\neq 0$	-0.004	-1.019
SR Own Advertising	$\bar{\alpha}_0^{sr}$	> 0	0.009 ***	14.132
<i>x Before Event</i>	$\bar{\alpha}_1^{sr}$	$\neq 0$	-0.004 ***	-2.888
<i>x Event</i>	$\bar{\alpha}_2^{sr}$	$\neq 0$	-0.006 ***	-5.520
<i>x After Event</i>	$\bar{\alpha}_3^{sr}$	$\neq 0$	-0.004 ***	-3.281
SR Own Price	$\bar{\gamma}^{sr}$	< 0	-0.579 ***	-20.884
SR Competitor Advertising	$\bar{\alpha}_0^{sr*}$	$\neq 0$	0.006 ***	9.643
<i>x Before Event</i>	$\bar{\alpha}_1^{sr*}$	$\neq 0$	-0.005 ***	-2.988
<i>x Event</i>	$\bar{\alpha}_2^{sr*}$	$\neq 0$	-0.004 **	-2.428
<i>x After Event</i>	$\bar{\alpha}_3^{sr*}$	$\neq 0$	-0.004 **	-2.233
SR Competitor Price	$\bar{\gamma}^{sr*}$	> 0	0.151 ***	5.974
LR Own Advertising	$\bar{\alpha}_0^{lr}$	> 0	0.014 ***	17.045
<i>x Before Event</i>	$\bar{\alpha}_1^{lr}$	$\neq 0$	-0.007 ***	-4.103
<i>x Event</i>	$\bar{\alpha}_2^{lr}$	$\neq 0$	-0.006 ***	-3.784
<i>x After Event</i>	$\bar{\alpha}_3^{lr}$	$\neq 0$	-0.002	-1.209
LR Own Price	$\bar{\gamma}^{lr}$	< 0	-0.612 ***	-18.576
LR Competitor Advertising	$\bar{\alpha}_0^{lr*}$	$\neq 0$	0.012 ***	9.492
<i>x Before Event</i>	$\bar{\alpha}_1^{lr*}$	$\neq 0$	-0.009 **	-2.617
<i>x Event</i>	$\bar{\alpha}_2^{lr*}$	$\neq 0$	-0.006 **	-2.085
<i>x After Event</i>	$\bar{\alpha}_3^{lr*}$	$\neq 0$	-0.004	-1.140
LR Competitor Price	$\bar{\gamma}^{lr*}$	> 0	0.327 ***	20.090
Adjustment	$\bar{\Pi}$	< 0	-0.584 ***	-120.162

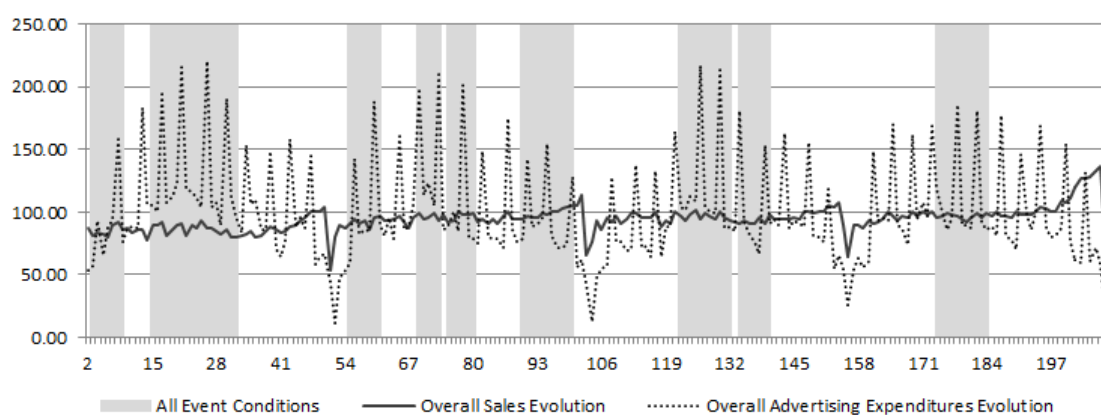
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Tests are one-sided if clear directional effects are expected (own advertising, own price, competitor price), two-sided if not (Rosenthal, 1991).

Table 6

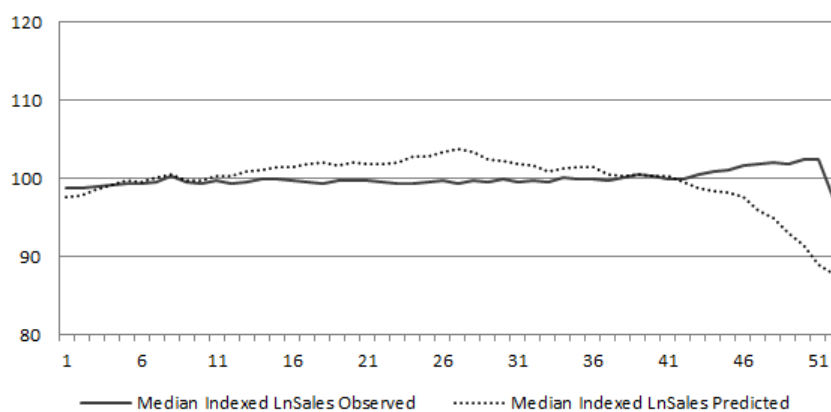
Advertising Cost Simulation Results.

	Benchmark	Fixed +25%	Fixed +50%	Dynamic +5% to +15%	Dynamic +10% to +30%
Intercept	0.007 ***	0.005 *	0.003	0.006 **	0.005 *
<i>x Before Event</i>	0.010 **	0.012 ***	0.014 ***	0.011 **	0.012 ***
<i>x Event</i>	0.012 ***	0.015 ***	0.017 ***	0.013 ***	0.014 ***
<i>x After Event</i>	0.006	0.010 **	0.013 ***	0.008 *	0.009 **
Holiday	-0.007	-0.007	-0.007	-0.007	-0.007
Qtrr1	-0.016 ***	-0.016 ***	-0.016 ***	-0.015 ***	-0.015 ***
Qtrr2	-0.019 ***	-0.019 ***	-0.019 ***	-0.019 ***	-0.019 ***
Qtrr3	-0.004	-0.004	-0.004	-0.004	-0.004
SR Own Advertising	0.009 ***	0.009 ***	0.009 ***	0.009 ***	0.009 ***
<i>x Before Event</i>	-0.004 ***	-0.004 ***	-0.004 ***	-0.004 ***	-0.004 ***
<i>x Event</i>	-0.006 ***	-0.006 ***	-0.006 ***	-0.006 ***	-0.006 ***
<i>x After Event</i>	-0.004 ***	-0.004 ***	-0.004 ***	-0.004 ***	-0.004 ***
SR Own Price	-0.579 ***	-0.575 ***	-0.573 ***	-0.576 ***	-0.573 ***
SR Comp Advertising	0.006 ***	0.007 ***	0.007 ***	0.006 ***	0.007 ***
<i>x Before Event</i>	-0.005 ***	-0.005 ***	-0.005 ***	-0.005 ***	-0.004 **
<i>x Event</i>	-0.004 **	-0.004 **	-0.004 **	-0.004 **	-0.004 **
<i>x After Event</i>	-0.004 **	-0.004 **	-0.005 **	-0.004 **	-0.005 **
SR Comp Price	0.151 ***	0.151 ***	0.152 ***	0.151 ***	0.151 ***
LR Own Advertising	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***
<i>x Before Event</i>	-0.007 ***	-0.007 ***	-0.007 ***	-0.007 ***	-0.007 ***
<i>x Event</i>	-0.006 ***	-0.006 ***	-0.006 ***	-0.006 ***	-0.006 ***
<i>x After Event</i>	-0.002	-0.002	-0.002	-0.002	-0.002
LR Own Price	-0.612 ***	-0.608 ***	-0.606 ***	-0.609 ***	-0.607 ***
LR Comp Advertising	0.012 ***	0.012 ***	0.012 ***	0.012 ***	0.012 ***
<i>x Before Event</i>	-0.009 **	-0.009 **	-0.008 **	-0.009 **	-0.009 **
<i>x Event</i>	-0.006 **	-0.007 **	-0.008 **	-0.006 **	-0.007 **
<i>x After Event</i>	-0.004	-0.004	-0.004	-0.004	-0.003
LR Comp Price	0.327 ***	0.328 ***	0.328 ***	0.327 ***	0.327 ***
Adjustment	-0.584 ***	-0.584 ***	-0.584 ***	-0.584 ***	-0.584 ***

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Tests are one-sided if directional hypotheses were formulated, two-sided if not (Rosenthal, 1991).

Fig. 1. Overall advertising and sales evolution.**Fig. 2.** Out-of-sample predictive performance.

A. Overall out-of-sample predictive performance



B. Out-of-sample predictive performance for median out-of-sample MAPE brand

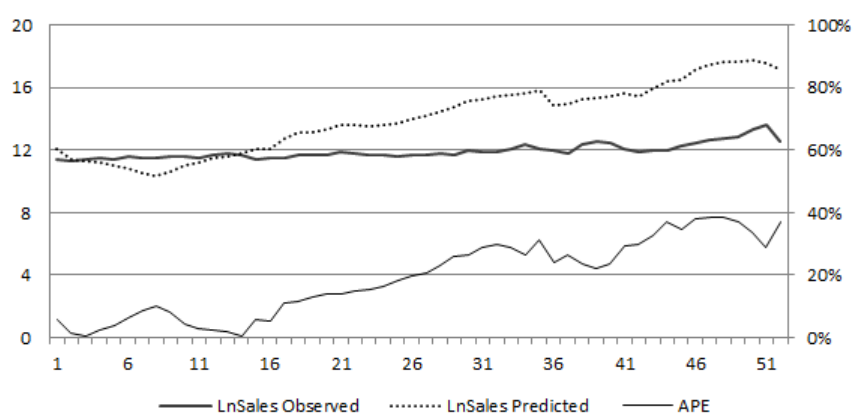
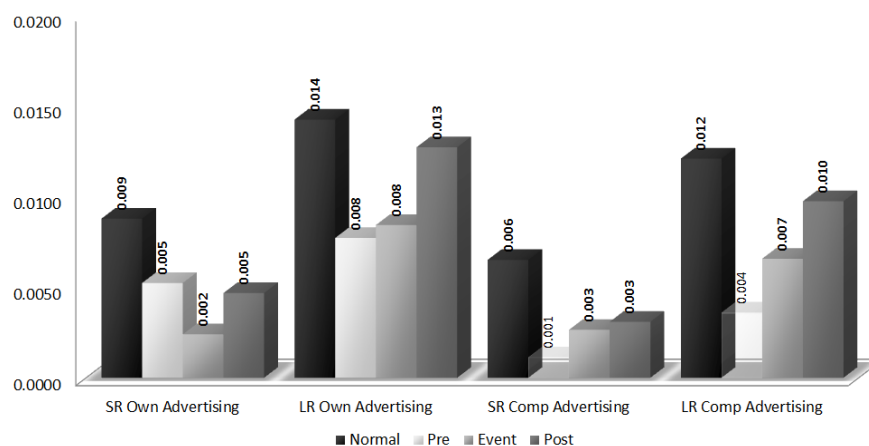
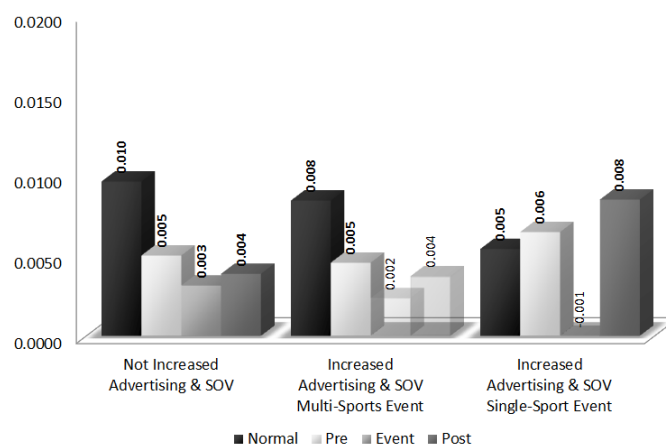


Fig. 3. Overall advertising elasticity evolution.

Note: The dark bars indicate significant elasticities, and the transparent bars indicate non-significant elasticities (at the 10% level).

Fig. 4. Own advertising elasticity evolution: Brands increasing SOV versus other brands.

A. Short-term own advertising elasticities.



B. Long-term own advertising elasticities.

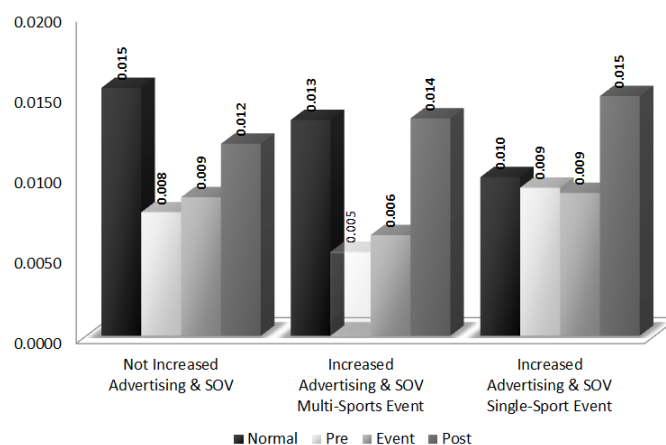
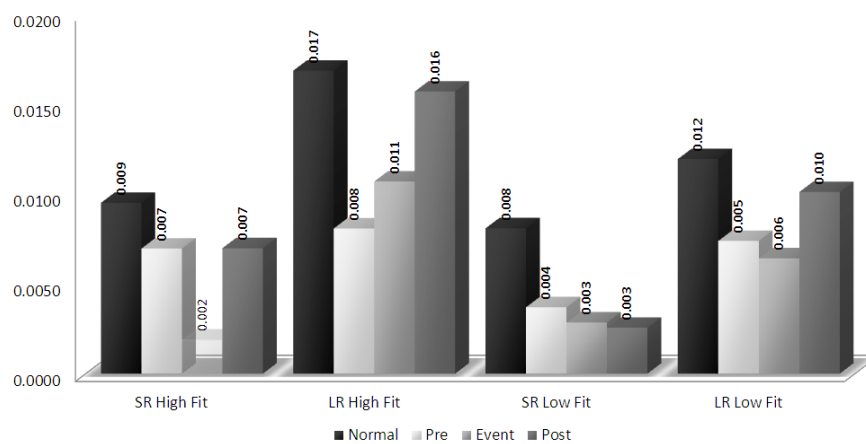


Fig. 5. Advertising elasticity evolution: high-fit versus low-fit categories.

APPENDIX

Estimation procedure

The proposed three-stage least squares methodology provides individual-brand-level estimates, while accounting for error correlations between brands in the same category. To estimate the focal model (Eq. 1), I multiply the adjustment parameter Π_b with the term between square brackets. I then derive the estimates for the parameters of interest (e.g., the long-term advertising effect) from the initial estimates for the products of parameters (e.g., $-\Pi_b \times \alpha_{b0}^{lr}$), and calculate the associated standard errors using the delta method (Greene, 2003, p. 175).

Although heterogeneity among brands, and thus individual brand estimates, is crucial for this study, the main goal is to provide empirical generalizations, and thus I apply the added Z method (Rosenthal, 1991),¹¹ which allows for the combination of the p -values across the different brands. This can be done for each effect in the model. From each brand-specific p -value (one-tailed), I derive the associated Z-score (standard-normal statistic). When no directional hypotheses are formulated, Zs with a direction that differs from the majority of the findings have the opposite sign. Subsequently, I sum the Zs and divide the sum by the square root of the number of included brands. This new Z-score is again standard-normal distributed and thus allows for the derivation of the associated p -values. The overall effect size is the weighted average response parameter across the included brands. The weight used is the inverse of the standard error of the estimate, normalized to one, which gives greater weight to estimates with higher reliability.¹²

¹¹ For recent applications of this method in marketing, see Kremer et al. (2008), Lamey et al. (2012), and Van Heerde et al. (2013).

¹² An alternative approach to generate overall insights consists of estimating a pooled model with fixed effects per brand. Although the outcomes of such a model are similar to those reported here, preference was given to the current methodology, because a Chow test indicated that the level of heterogeneity among brands was prohibitive to pooling.